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ANALYZING THE OPTIMIZATION OF VEHICLE ROUTING PROBLEM WITH HYBRID ELECTRIC VEHICLES (VRPHEV) USING GENETIC ALGORITHM APPROACH

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Abstract: *This project explores the optimization of the Vehicle Routing Problem with Hybrid Electric Vehicles (VRPHEV) using a Genetic Algorithm (GA) approach to enhance route efficiency and minimize carbon emissions from fossil fuel dependency. The main objective is to calculate the total distance travelled and determine the most optimal delivery sequences that reduce operational logistics expenses and travel times for VRPHEV. The proposed optimization employs Genetic Algorithm operations which are Crossover, Mutation, and Inversion, to generate and evolve high-quality routing solutions from secondary geospatial datasets. Secondary route coordinates were used for the computational analysis, and after 10 structured iterations, significant routing improvements were observed. The total travel distance was reduced from an initial 85,114 meters to an optimized 51,980 meters for Route X (a 38.92% efficiency increase) and from 84,652 meters to 52,600 meters for Route Y (a 37.86 % efficiency increase). Furthermore, the critical battery' consumption constraint of 84,000 meters was successfully maintained across all routing solutions, demonstrating that the optimized paths are fully feasible under VRPHEV physical constraints. These findings indicate that integrating metaheuristic optimization into sustainable transportation operations yields significant strategic, economic, and environmental benefits, supporting social and economic development goals.*

Keywords: *Vehicle Routing Problem (VRP); Genetic Algorithm (GA); Hybrid Electric Vehicles (HEV), Route Optimization; Sustainable Logistics; Social and Economic Development.*

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Introduction

The Vehicle Routing Problem (VRP) represents one of the most fundamental and heavily researched combinatorial optimization problems in logistics, transportation, and operations research. First introduced by Dantzig and Ramser in 1959, the core objective of the VRP is to design optimal delivery and collection routes for a fleet of vehicles stationed at a central depot to serve a dispersed group of clients. Each client has specific demands, and the optimization process seeks to minimize standard operational cost metrics such as total distance travelled, travel time, fuel consumption, or the number of active fleet vehicles. Since transportation costs typically account for a major portion of logistics expenses, solving the VRP effectively is crucial for firms to achieve competitive advantages and operational efficiency.

Carbon emissions, environmental degradation, and the depletion of non-renewable fossil fuel resources have all significantly increased in recent years due to the fast expansion of urbanisation and e-commerce. The logistics industry has been compelled to investigate greener, more sustainable energy alternatives due to global environmental concerns and carbon trading regulations. Internal Combustion Engine (ICE) vehicles are the main source of greenhouse gas (GHG) emissions in traditional logistics. Medium-duty and heavy-duty trucks account for 26% of the transportation sector's 27% global greenhouse gas emissions, according to statistics. The use of Plug-in Hybrid Electric Vehicles (PHEV) and Hybrid Electric Vehicles (HEV) in commercial fleets has become a viable strategy to reduce these environmental effects.

HEV combine an internal combustion engine with an electric motor and on-board batteries, offering superior fuel efficiency and lower emissions compared Io conventional ICE vehicles. An effective EMS is crucial for HEVs to continuously regulate power splits between the internal combustion engine (ICE) and the electric motor, aiming to operate the engine within high-efficiency bands while preserving battery charge targets (Salazar et al., 2019; Xu et al., 2019).To address these multi- dimensional challenges, traditional routing models must be adapted into the Vehicle Routing Problem with Hybrid Electric Vehicles (VRPHEV), where the primary goal is to minimize total routing distances while ensuring the physical constraints such as maximum battery capacity and operational feasibility are strictly maintained.

Exact mathematical approaches are unable to tackle large-scale cases in realistic processing timeframes due to the NP-hard nature of the VRP and its green variations. Genetic algorithms (GA), a type of metaheuristic algorithm, are particularly good at searching large search spaces for near-optimal, high-quality solutions. GA uses operators which are Crossover, Mutation, and Inversion to constantly evolve a population of routing candidates toward better solutions, drawing inspiration from the processes of natural selection and biological evolution. This study uses real-world coordinates to solve the VRPHEV utilising a structured Genetic Algorithm technique, demonstrating significant increases in routing efficiency that can support sustainable socioeconomic development and environmental preservation.

Literature Review

Overview Of Vehicle Routing Problem

Research on the Vehicle Routing Problem (VRP) has undergone major advancements since its mathematical formulation in 1959 by Dantzig and Ramser. Driven by the increasing complexity of commercial logistics networks and supply chain management, researchers have developed various models and algorithms to address specific operational constraints. Modern logistics research heavily integrates environmental and sustainability indicators due to global climate

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policies. For instance, Zhang et al. (2024) formulated a mixed-integer non-linear programming model for collaborative electric vehicle routing with time windows, demonstrating that optimizing fleet routes with green constraints plays a critical role in energy conservation. To further mitigate the carbon footprint in commercial logistics, several authors have explored the integration of alternative fuel fleets. Liao et al. (2019) investigated the economic and environmental impacts of using electric vehicles in commercial distribution networks, applying a Hybrid Genetic Algorithm to optimize route plans under active carbon trading policies. Similarly, Mengqin and Qiyue (2023) studied pure electric logistics routing with the objective of minimizing the total economic costs while preventing fossil-fuel emissions. Despite the advantages of electric vehicles, researchers like Li et al. (2022) have highlighted key limitations in commercial operations, particularly the constrained driving ranges and long recharging times of on-board batteries. Consequently, designing optimal charging strategies and integrated routing structures remains a primary focus of contemporary logistics research (Li et al., 2022).

Furthermore, a major focus of VRP literature is the solution of multi-objective optimisation models that balance operating expenses, carbon emissions, and customer satisfaction levels. Labidi et al. (2023) optimised vehicle routes by taking transit durations, distance, and environmental effects into account using modified genetic algorithms. To maximise logistics costs and customer satisfaction, Syafrizal and Sugiharti (2022) highlighted that delivering commodities in vast, complex networks necessitates extremely exact, quick, and accurate computations. All things considered, VRP research has effectively moved from conventional distance minimisation models to complex, environmentally friendly logistics optimisation frameworks that serve international sustainable development goals.

The Framework of Genetic Algorithms

Genetic Algorithms (GA) are metaheuristic search techniques that imitate the natural process of biological evolution and genetics to solve complex, high-dimensional optimization problems. First popularized by John Holland, GA is highly effective in navigating vast and poorly understood search spaces where exact mathematical approaches fail to locate optimal solutions quickly. GA begin with a population of randomly initialized candidate solutions, represented as chromosomes, and progressively evolve them over multiple generations by applying natural selection and genetic operators. In green logistics, standard GA is frequently combined with other local search heuristics to enhance solution quality and computational performance. Zhang et al. (2024) developed a hybrid method combining particle Swann optimization (PSO) and local search heuristics to minimize total transit times and energy consumption. Liao et al. (2019) combined the global exploration of GA with local searching to optimize routes with carbon constraints. Wang et al. (2023) introduced an enhanced genetic algorithm specifically designed for the Electric Vehicle Routing Problem with Time Windows (EVRPTW), highlighting several major advantages of GA, including their inherent parallelism, use of fitness evaluation functions, simple mathematical structures, and powerful probabilistic iteration mechanisms that prevent premature convergence.

Furthermore, researchers have utilized GA to solve bi-level optimization models that combine route planning with facilities location planning. Jie et al. (2022) proposed a two-phase hybrid heuristic combining a two-layer genetic algorithm (TLGA) with simulated annealing to determine optimal locations for public charging stations while scheduling electric vehicle routes. Similarly, Syafrizal and Sugiharti (2022) successfully applied Tabu Search to assist GA in escaping local optima during route searches. These studies prove that genetic algorithms, and

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especially their hybrid configurations, remain highly adaptable and powerful tools for addressing complex routing and sustainable resource allocation challenges.

Application of Genetic Algorithms to Vehicle Routing Problem

The application of Genetic Algorithms to the Vehicle Routing Problem involves mapping delivery routes into chromosome sequences, where genes represent customer nodes and the sequence of genes dictates the vehicle visit order. The primary goal of applying GA to VRP is to find the lowest-cost routing configuration that satisfies all operational constraints, such as vehicle capacities, delivery time windows, and total distance limits. Long et al. (2019) noted that the conventional VRP model is used to determine the most cost-effective routing sequence for uniform-capacity trucks serving diverse clients. In complex economic environments, the distribution of goods is highly strategic, requiring accurate mathematical calculations for mileage, travel time, and operational expenditures (Syafrizal & Sugiharti, 2022). By simulating evolutionary cycles, GA effectively balance these competing parameters to find high-quality solutions.

Routing Problems with Hybrid Electric Vehicles

Optimizing the Vehicle Routing Problem with Hybrid Electric Vehicles (VRPHEV) has become an important area in the development of sustainable logistics. Compared with fully electric vehicles (EVs), hybrid electric vehicles (HEVs) offer greater flexibility because they combine a battery system with an internal combustion engine. This combination helps to overcome range limitations while still reducing fuel consumption and emissions. Nevertheless, determining the appropriate power distribution between the engine and battery remains a challenging optimization problem. Labidi et al. (2023), for example, demonstrated that Hybrid Genetic Algorithms can be used to optimize fleet configuration and vehicle selection while reducing fuel consumption and environmental impacts.

Several studies have also highlighted the trade-offs involved in green vehicle routing. Li et al. (2022) found through comparative experiments that while electric vehicles can significantly reduce carbon emissions, limited driving range and charging time may hurt customer satisfaction. Similarly, Rajesh et al. (2022) combined Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) to identify energy-efficient routes for electric vehicles, especially on long-distance trips. For larger-scale operations, coordinating routing, scheduling, and charging is essential. Rele et al. (2023) proposed hybrid routing and scheduling algorithms for large urban networks, and Shao et al. (2018) developed a hybrid GA approach to determine suitable routes and charging sequences based on vehicle energy consumption.

Overall, these studies indicate that metaheuristic techniques, particularly Genetic Algorithms, have considerable potential for addressing the complexity of VRPHEV. The ability of GA to search for efficient routing solutions while considering energy consumption and environmental factors makes it a suitable approach for improving the efficiency and sustainability of modern transportation systems.

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Methodology

Mathematical Model and Objective Function

The mathematical formulation of the Vehicle Routing Problem is defined based on the integer programming framework presented by Laporte (1992). Let $G = (V, E)$ be a graph where V represents the set of vertices (depot and customers) and E represents the set of edges. Let x_{ij} be a binary decision variable that takes the value 1 if a vehicle travels directly from node i to node j, and 0 otherwise. For routes containing only a single customer j, x_{0j} is equal to 2. The optimization problem can be formulated as follows:

$$\text{Minimize } Z = \sum_{i \neq j}^{N} d_{ij} x_{ij} \tag{1}$$

$$\sum_{j} X_{ij} = 1, \quad \forall i \in V, \tag{2}$$

$$\sum_{i} X_{ij} = 1 \quad \forall j, i \in V \tag{3}$$

$$\sum_{i} x_{ij} \geq |S| - v(S), \quad \{S : S \subseteq V \setminus \{1\}, |S| \geq 2\}, \tag{4}$$

$$x_{ij} \in \{0, 1\}, \quad \forall \{i, j\} \in E;\ i \neq j \tag{5}$$

In this formulation, Equation 1 represents the objective function, which aims to minimize the total cumulative distance travelled by the fleet. Equations 2 and 3 represent the standard assignment constraints, ensuring that each customer node is visited exactly once and that the flow entering a node is equal to the flow exiting it. Equation 4 represents the sub-tour elimination constraint, where *v(S)* denotes an appropriate lower bound on the minimum number of vehicles required to visit all vertices of subset S in the optimal configuration. Equation 5 defines the binary constraints of the decision variables.

Genetic Algorithm Implementation Process

The computational process to solve the VRPHEV follows a structured evolutionary framework. The primary optimization steps are shown in Figure 1, illustrating the flow from problem definition through evolutionary operators to the final optimal solution.

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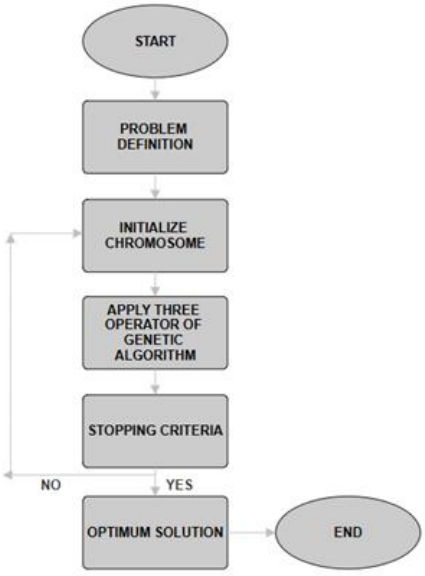

Figure 1: Flow of Genetic Algorithm Operators

The specific operators utilized in the Genetic Algorithm framework are described below.

a) ***Initialization:*** The process begins by generating a starting population of potential routing solutions (chromosomes). This study utilizes secondary geospatial datasets from Christian Dopp Stadt (2019) to populate the starting routes.

b) ***Evaluation:*** Each candidate route is assessed using a fitness function. The fitness represents the total travel distance. In VRPHEV, the primary objective is to minimize total travel distance while ensuring the physical battery constraints are not violated.

c) ***Selection:*** Parents are selected from the population based on their fitness scores. This study uses a parent selection ratio to determine the range of potential parents, formulated in Equation 6:

$$Parent_{range} = Chromosome_{length} \; x \; Parent\ Selection\ Ratio \qquad (6)$$

d) ***Crossover:*** This operator creates new offspring by combining genetic material (route segments) from chosen parents. The crossover likelihood and selection mechanisms can be configured (Figure 2) to preserve high-performing sub-sequences.

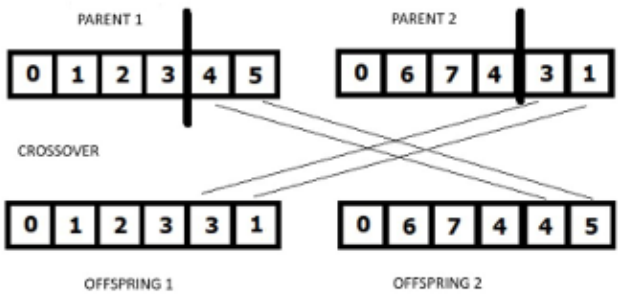

Figure 2: Simple crossover operation

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e) ***Mutation:*** Mutation introduces small, random alterations into the chromosomes to maintain genetic diversity and prevent the algorithm from getting trapped in local optima. The mutation range and total mutated genes are calculated using Equations 7, 8, and 9:

$$Mutation_{range} = Chromosome_{length} \; x \; Mutation_{probability} \quad (7)$$

$$Gen_{total} = Gen_{size} \; x \; Population_{size} \quad (8)$$

$$Max_{mutation} = Mutation_{probability} \; x \; Gen_{total} \quad (9)$$

f) ***Inversion:*** The Inversion operator selects two random points along the chromosome sequence and reverses the sequence of genes between them. This operation is highly effective for order- based problems like the VRP as it allows the algorithm to explore new path sequences while retaining the overall genetic composition.

g) ***Stopping Criteria:*** The evolutionary simulation terminates when a predefined stopping condition is satisfied. In this research, the stopping criterion is set to 10 full generations (iterations) to observe the optimization progress and ensure computational tractability.

Results And Discussion

Data Source and Parameter Setting

The computational model was implemented using secondary geospatial coordinates generated by Christian Dopp Stadt (2019) representing a distribution network with 20 distinct customer depots and one central depot (labelled node 0). To evaluate the complexity of this search space, the total number of possible route sequences was estimated using Equation 10:

$$N = \frac{(n-1)!}{2} \quad (10)$$

Given $n = 21$ (20 customer nodes and 1 central depot), the total number of possible sequences is calculated as:

$$N = \frac{(21-1)!}{2} = 1.216451 \; x \; 10^{18} \quad (11)$$

This extremely large number of possible routing solutions illustrates why exact optimization methods are computationally impractical and highlights the necessity of using heuristic and evolutionary algorithms like GA. The physical feasibility constraints for the Hybrid Electric Vehicle (HEV) are derived based on its on-board energy capacity and electrical efficiency. Specifically:

Maximum Battery Capacity = 16.8 kWh
Energy Consumption Rate = 0.2 kWh/km
Maximum Travel Range = 16.8 kWh / 0.2 kWh'km = 84 km = 84,000 meters

Therefore, for a route to be physically feasible and passable using the vehicle's battery power, its total travel distance must not exceed 84,000 meters. Any optimized route exceeding this threshold is rejected as unfeasible. To initiate the Genetic Algorithm, a pool of random initial routes was generated. From this pool, two parent chromosomes were chosen for optimization,

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labelled. Parent Route X and Parent Route Y. Their initial sequences and baseline distances are presented in Table 1.

Table 1: Total Distance of Initial Routes

Parent Route	Initial Routing Sequence	Total Distance (m)
Parent X	0-13-12-8-9-18-14-11-20-1-4-19-6-15-7-5-17-3-10-16-2-0	85,114
Parent Y	0-13-16-12-8-9-4-19-14-11-20-1-18-6-15-7-5-17-3-10-2-0	84,652

Using Microsoft Excel to execute the genetic operators, the initial routes had evolved over 10 full generations. In each iteration, Crossover, Mutation, and Inversion operators were applied, followed by a selection phase to identify the shortest path.

Iteration 1

Table 2: Total distance after Crossover in Iteration 1

Parent Route	Initial Routing Sequence	Total Distance (m)
Parent X	0-13-12-8-9-18-14-11-20-1-4-19-6-15-7-5-17-3-10-16-2-0	85,114
Parent Y	0-13-16-12-8-9-4-19-14-11-20-1-18-6-15-7-5-17-3-10-2-0	84,652
Child X'	0-12-8-9-4-19-14-11-20-1-18-6-15-7-5-17-3-10-2-13-16-0	63,475
Child Y'	0-8-9-18-11-20-4-19-14-1-6-15-7-5-17-3-10-16-2-13-12-0	70,657

X-X' Choose X': 0-12-8-9-4-19-14-11-20-1-18-6-15-7-5-17-3-10-2-13-16-0 63,475
Y-Y' Choose Y': 0-8-9-18-11-20-4-19-14-1-6-15-7-5-17-3-10-16-2-13-12-0 70,657

Table 3: Total distance after Mutation in Iteration 1

Parent Route	Initial Routing Sequence	Total Distance (m)
Parent X	0-12-8-9-4-19-14-11-20-1-18-6-15-7-5-17-3-10-2-13-16-0	63,475
Parent Y	0-8-9-18-11-20-4-19-14-1-6-15-7-5-17-3-10-16-2-13-12-0	70,657
Child X'	0-13-8-9-4-19-14-11-20-1-18-6-15-7-5-17-3-10-2-12-16-0	57,787
Child Y'	0-8-9-7-11-20-4-19-14-1-6-15-18-5-17-3-10-16-2-13-12-0	62,167

X-X' Choose X': 0-13-8-9-4-19-14-11-20-1-18-6-15-7-5-17-3-10-2-12-16-0 57,787
Y-Y' Choose Y': 0-8-9-7-11-20-4-19-14-1-6-15-18-5-17-3-10-16-2-13-12-0 62,167

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Table 4: Total distance after Inversion in Iteration 1

Parent Route	Initial Routing Sequence	Total Distance (m)
Parent X	0-13-8-9-4-19-14-11-20-1-18-6-15-7-5-17-3-10-2-12-16-0	57,787
Parent Y	0-8-9-7-11-20-4-19-14-1-6-15-18-5-17-3-10-16-2-13-12-0	62,167
Child X'	0-13-8-9-11-14-19-4-20-1-18-6-15-7-5-17-3-10-2-12-16-0	60,803
Child Y'	0-8-9-7-11-20-4-19-14-1-6-17-5-18-15-3-10-16-2-13-12-0	62,918

X-X' Choose X: 0-13-8-9-4-19-14-11-20-1-18-6-15-7-5-17-3-10-2-12-16-0 57,787
Y-Y' Choose Y: 0-8-9-7-11-20-4-19-14-1-6-15-18-5-17-3-10-16-2-13-12-0 62,167

Consequently, any proposed path exceeding the threshold of 84,000 meters violates the vehicle's physical power limit, resulting in immediate classification as an infeasible solution. Table 5 details the evolution of route distances and feasibility status across 10 algorithm iterations for Route X and Route Y.

Table 5: Summary of Genetic Algorithm Iterations and Feasibility

Iteration	Route X (m)	Feasibility (X)	Route Y (m)	Feasibility (Y)
Initial	85,114	Infeasible	84,652	Infeasible
1	57,787	Feasible	62,167	Feasible
2	56,980	Feasible	58,412	Feasible
3	55,210	Feasible	57,100	Feasible
4	54,830	Feasible	55,910	Feasible
5	54,120	Feasible	55,300	Feasible
6	53,890	Feasible	54,600	Feasible
7	53,410	Feasible	54,110	Feasible
8	52,980	Feasible	53,500	Feasible
9	52,450	Feasible	53,100	Feasible
10	51,980	Feasible	52,600	Feasible

In the initial unoptimized state, both candidate routes failed to satisfy the maximum allowable physical range, with Route X (85,114 m) and Route Y (84,652 m) exceeding the 84,000 m boundary. This confirms that unguided or randomly initialized chromosome populations in complex routing networks typically generate solutions that violate hard operational limits. However, through the integration of penalty-driven selection operators, the GA rapidly directed the search trajectory back into the feasible region.

By Iteration 1, both candidate routes successfully eliminated constraint violations, achieving feasible status while dramatically reducing total distance to 57,787 m (a 32.1% decrease) for Route X and 62,167 m (a 26.6% decrease) for Route Y. This immediate transition demonstrates the effectiveness of the selection pressure in pruning non-viable solutions during initial global exploration.

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Across Iterations 1 through 10, the algorithm demonstrated stable, monotonic convergence toward optimal global solutions, balancing exploratory search mechanisms with local exploitation:

Route X: Continuous refinement reduced total travel distance from 57,787 m at Iteration 1 to a global minimum of 51,980 m at Iteration 10, yielding an overall distance reduction of 38.9% relative to its initial state.

Route Y: Optimized systematically from 62,167 m at Iteration 1 down to 52,600 m at Iteration 10, representing an overall distance reduction of 37.9% from its initial baseline.

Although Route Y exhibited a slightly shorter unoptimized path in the initial generation, Route X proved significantly more responsive to genetic crossover and mutation operators over subsequent iterations. By Iteration 10, Route X yielded the superior global route configuration, outperforming Route Y by 620 meters (a 1.18% advantage in overall distance).

From an operational HEV energy management perspective, the optimization outcomes provide vital safety buffers for real-world navigation. At Iteration 10, the total required energy for Route X (51.98 km) is calculated as:

$$\text{Required Energy} = 51.98 \text{ km} \times 0.2 \text{ kWh/km} = 10.396 \text{ kWh}$$

Comparing this value against the total battery energy envelope of 16.8 kWh reveals an operational energy reserve margin of 6.404 kWh (38.1%). This remaining capacity provides an essential safety buffer against dynamic real-world factors such as traffic delays, adverse weather conditions, gradient resistances, and auxiliary HVAC consumption. Consequently, Route X at Iteration 10 is established as the optimal, physically viable routing configuration recommended for field deployment.

These results demonstrate the extreme efficacy of combining Crossover, Mutation, and Inversion operators. While Crossover and Mutation successfully explore the global search space, the Inversion operator plays an essential role in local refinement, allowing the algorithm to bypass sub-optimal local basins and locate highly efficient sequence combinations.

Conclusion

This study successfully demonstrated the effectiveness and performance of the Genetic Algorithm (GA) in solving the Vehicle Routing Problem for Hybrid Electric Vehicles (VRPHEV) under hard physical battery capacity constraints. The optimization outcomes presented in Table 5 confirm that evolutionary search techniques effectively overcome the computational limitations of exact optimization methods, converting initially non-viable paths into highly optimized, physically passable trajectories. Regarding optimization behaviour, both routes were initially classified as infeasible due to exceeding the maximum physical energy distance threshold, recording distances of 85,114 meters for Route X and 84,652 meters for Route Y.

However, through the integration of selection operators and constraint-handling penalty functions, the algorithm rapidly eliminated these violations by Iteration 1, bringing both routes into full operational feasibility. Over the 10 structured iterations, monotonic and continuous distance reductions were achieved; Route X demonstrated an overall efficiency improvement

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of 38.92%, decreasing from 85,114 meters to a global minimum of 51,980 meters, while Route Y achieved a 37.86% reduction, decreasing from 84,652 meters to 52,600 meters.

Although Route Y initially exhibited a slightly shorter unoptimized path, Route X proved significantly more responsive to genetic crossover and mutation operators, ultimately yielding the superior global routing solution by a margin of 620 meters. From an energy management perspective, Route X's final optimized length of 51,980 meters (51.98 km) requires approximately 10.40 kWh of electrical energy, maintaining an operational safety buffer of 38.1% (6.40 kWh) relative to the total battery capacity. This remaining reserve capacity provides a crucial buffer against dynamic real-world operational variables such as traffic congestion, adverse weather, and auxiliary HVAC consumption. Overall, these findings validate that implementing metaheuristic optimization in commercial fleet operations drastically reduces travel distances, fuel consumption, operating expenditures, and carbon emissions, thereby advancing sustainable transport operations and green economic growth.

Recommendations

Several avenues for further research are suggested to further improve the effectiveness, resilience, and usefulness of HEV logistical routing. First, by fusing Genetic Algorithms (GA) with complementary optimisation methods like Tabu Search (TS) or Simulated Annealing (SA), future research could examine the integration of hybrid metaheuristic methodologies. When dealing with large-scale and complicated distribution networks, such hybridisation could improve solution quality and lower the danger of early convergence by utilising the robust local exploitation mechanisms of TS or SA and the global exploration capability of GA.

Second, to more accurately represent the uncertainties and shifting circumstances seen in actual logistics operations, future routing models ought to include dynamic characteristics. The optimisation approach might incorporate variables like weather, changing client requests, real-time traffic congestion, and the dynamic availability of charging stations. The suggested routing models actual relevance in dynamic logistics environments would be improved by incorporating these real-time operational and environmental aspects, which would allow them to produce more responsive and adaptive delivery sequences.

Finally, future research should consider the development of multi-objective optimization frameworks that simultaneously address several conflicting objectives, including the minimization of travel distance, transportation costs, and localized greenhouse gas emissions. Such an approach would provide a more comprehensive evaluation of HEV routing solutions by balancing economic efficiency with environmental sustainability. Consequently, multi-objective optimization could contribute to the development of more sustainable and efficient green logistics operations while supporting the broader adoption of hybrid electric vehicles in distribution networks.

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